FINGER VEIN BIOMETRIC AUTHENTICATION USING DEEP LEARNING TECHNIQUES WITH HYBRID LABELLING AND DATA AUGMENTATION

SYNOPSIS

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1. INTRODUCTION

Biometric authentication has become essential for secure and reliable identity verification. Among various biometric modalities, finger vein authentication has emerged as a highly secure option due to its reliance on the unique, internal vascular patterns within the finger. Finger vein biometric technology uses near-infrared imaging to capture an individual's vein structure, making it challenging to forge and providing a robust level of security. This technology is widely applied across financial services, healthcare, government, corporate security, education, personal security, transportation, retail, hospitality, military, and airports [1-2].

Despite its advantages, finger vein biometrics faces practical challenges when applied in dynamic environments. The accuracy and reliability of finger vein recognition systems are heavily influenced by the quality of feature extraction techniques and environmental factors while scanning images, such as motion artifacts, lighting, and finger positioning. Movement of finger during image capture, such as minor hand shifts, can significantly affect image quality and reduce model accuracy, making the system susceptible to false matches or rejections.

Traditional finger vein recognition systems rely on handcrafted features and classical machine learning algorithms, which face limitations in adaptability and accuracy under variable conditions. Recent advancements in deep learning techniques have demonstrated the potential to automatically extract complex patterns from raw image data, addressing these challenges. Finger vein datasets, by their nature, are usually limited in size. Augmentation serves to address this limitation by increasing the dataset size and diversity. Through augmentation, models are exposed to a wide range of variations that may mimic real-world conditions, such as changes in illumination, finger orientation, scale, and noise. Labelling the images allows the deep learning model to learn features that are specifically related to vein and background regions. Labelled images help in reducing ambiguity during the training phase leading to faster convergence of the model and significantly improving its overall performance. The proposed solution is designed to be adaptive, efficient, and robust, enabling high accuracy in diverse conditions.

2. LITERATURE SURVEY

Deep learning approaches have demonstrated superior performance in various image recognition tasks, including finger vein recognition. Radzi et al. [3] proposed a robust approach for finger vein biometric identification by leveraging convolutional neural networks (CNN) combined with the stochastic diagonal Levenberg–Marquardt algorithm. Huang et al. [4] utilized deep CNNs in their DeepVein model to achieve state-of-the-art biometric verification accuracy, highlighting the critical role of data quality and quantity in optimizing performance. Qin et al. [5] discussed the use of convolutional neural networks (CNN) for labelling and training, to enhance the accuracy of finger-vein verification by effectively extracting and recovering vein patterns. Hong et al. [6] investigated the use of CNNs for finger-vein recognition with data augmentation to enhance the training process, specifically using only translation for augmentation. Jalilian et al. [7] explored the use of semantic segmentation convolutional neural networks (CNN) for finger-vein recognition, emphasizing the importance of training data quality, comparing manually annotated data with automatically generated labels, and found that automatically generated labels can enhance the network's performance, leading to higher recognition accuracy.

Fang et al. [8] proposed a two-stream convolutional network for finger vein verification, improving accuracy by processing dual input streams, but its effectiveness is limited by insufficient training samples and inadequate preprocessing for rotation and displacement issues. Kim et al. [9] investigated the integration of finger-vein and finger shape biometrics using a deep CNN and NIR camera, improving recognition accuracy but facing challenges with misalignment due to finger position changes during image capture.

Gumusbas D et al. [10] introduced a Capsule Network-based approach for finger-vein recognition, effectively addressing limited sample sizes and spoofing challenges, though its reliance on low-resolution images may limit detail capture.

Kuzu et al. [11] proposed a real-time biometric recognition method combining CNNs for feature extraction and LSTMs for temporal dependencies, facing challenges with high computational demands. Noh et al. [12] enhanced finger vein recognition by integrating texture and shape images via score-level fusion using a deep CNN, improving robustness to noise and illumination changes but facing challenges with increased processing time and preprocessing complexity. Huang et al. [13] combined ResNet for deep feature extraction with UNET for spatial attention and bias field correction, enhancing robustness and accuracy but facing challenges with high computational demands and extensive training data requirements.

Li J et al. [14] explored finger vein verification using deep learning with a triplet loss function, achieving high accuracy and generalizability through cross-validation, though challenges remain with limited images in datasets. Krishnan H et al. [15] proposed a transfer learning-based model enhanced by data augmentation to improve finger-vein recognition under suboptimal conditions, and it highlights the need for validation with larger and more diverse datasets, including synthetic images. Devkota et al. [16] proposed a Squeeze-and-Excitation-DenseNet model with channel attention and hybrid pooling for enhanced finger vein recognition, improving accuracy and robustness but requiring data augmentation to address image quality variations.

3. PROBLEM DEFINITION

Enhancing finger vein recognition involves tackling several critical challenges to improve the accuracy and reliability of this biometric technology. One major issue is data scarcity, as obtaining a large and diverse dataset of finger vein images can be difficult, limiting the effectiveness of machine learning models. Additionally, optimizing training time efficiency in deep learning approaches is essential to make the models practical and scalable for real-world applications. Finally, it is crucial to integrate techniques that account for the temporal behaviour of fingers during image capture, as slight movements or variations in finger positioning can affect the consistency and accuracy of vein pattern recognition. To address these challenges, designing an efficient, motion-tolerant deep learning model for finger vein recognition for human authentication using contactless acquisition devices is necessary.

4. OBJECTIVES OF THE RESEARCH

The following are the main objectives of the research:

- To identify an efficient deep learning algorithm for finger vein recognition that achieves high accuracy
- To identify a finger vein labelling method for extracting baseline patterns from raw images, to reduce training time for deep learning algorithms.
- To augment the dataset to enhance accuracy, robustness, and prevent overfitting by increasing the diversity and quantity of training data.
- To develop a motion tolerant deep learning model to improve the finger vein recognition performance in a contactless acquisition device.

5. RESEARCH METHODOLOGIES

The model architecture was initially developed using the THU-FVFDT1 dataset [19], which includes 720x576-pixel finger vein images from 220 subjects, captured under nonuniform illumination, enabling quicker training and retraining. To confirm the performance on a larger scale, the SDUMLA-HMT dataset [20], containing 3816 images from 106 individuals across multiple fingers and sessions, was employed.

5.1 Finger vein recognition using modified UNET and VGG16

Traditional finger vein recognition systems have primarily relied on handcrafted features and classical machine learning algorithms, which involve manually extracting features such as vein bifurcations and endings for classification. However, these methods often struggle with adaptability and accuracy, especially under varying conditions like changes in lighting, finger positioning, and image quality. This limitation has driven the need to explore more advanced methods that can improve the system's reliability and effectiveness.

Recent developments in deep learning, particularly with convolutional neural networks (CNNs), offer a promising solution by enabling the automatic extraction and classification of complex patterns from raw images. In the proposed method two approaches were explored: a modified U-Net architecture [12] combined with a fully connected layer for precise segmentation and classification of vein patterns, and the VGG16 CNN model [13], known for its robust feature extraction capabilities. The modified U-Net effectively segments detailed structures within images, while VGG16’s hierarchical feature extraction captures intricate vein patterns, providing resilience to variations in lighting, positioning, and image quality. The performance of modified UNET and VGG16 architectures is evaluated to identify the model suited for finger vein recognition tasks.

5.2 Finger Vein Image Labelling using hybrid algorithm for faster convergence and reduced training time

Finger vein image labelling involves marking each pixel in an image as either vein or background, enabling deep learning models to learn vein patterns with high precision. This pixel-level labelling strengthens the model's ability to differentiate vein structures from

background regions, making it more resilient to variations in lighting, positioning, and environmental factors. Accurate labelling is crucial for enhancing the model's recognition accuracy and robustness in biometric identification applications.

To ensure consistent and precise labelling, this work applies three prominent automated algorithms: the Local Maximum Curvature (LMC) algorithm, the Wide Line Detector (WLD), and the Repeated Line Tracking (RLT) algorithm. LMC focuses on the centre lines of veins, providing a clear vein structure, while WLD detects veins by analysing the local brightness contrasts around each pixel. RLT tracks the dark lines in the image, effectively capturing vein patterns. By combining results from these algorithms, an improved, highly accurate labelled dataset is created, providing a strong foundation for the deep learning model to learn and generalize from these annotated vein images.

5.3 Augmenting datasets using conventional transformation methods and conditional Generative Adversarial Networks.

Dataset augmentation is essential in machine learning for enhancing model performance and resilience by generating additional training samples through various transformations. By artificially expanding the dataset size and diversity, augmentation helps to address overfitting, where a model performs well on training data but poorly on new, unseen data. This is particularly valuable for finger vein recognition systems, where databases often contain limited images per subject. With fewer samples, models struggle to learn distinct vein patterns accurately, resulting in weaker generalization and reduced verification accuracy.

To capture the natural variability in vein patterns, a larger and more diverse dataset that includes variations in rotation, displacement, and lighting is critical. Augmentation helps to train the models to recognize vein patterns under different scenarios, supporting better generalization and improved performance in various applications. In this work, two augmentation strategies are employed: Conventional Transformations and Generative Adversarial Networks (GANs). Conventional methods apply predefined geometric changes, while GANs, using deep learning, generate realistic and varied images. By combining these approaches, the augmented dataset utilizes the strengths of each method, producing a robust training set for more effective deep learning model training.

5.4 Adaptive finger vein recognition using motion-tolerant VGG16 and LSTM architectures

Implementing finger vein authentication in real-world scenarios is challenging due to motion artifacts and varying image capture conditions, which can impact system reliability and accuracy. To address these issues, a motion-tolerant deep learning model is proposed that combines the VGG16 convolutional neural network (CNN) for robust feature extraction and Long Short-Term Memory (LSTM) networks for managing sequential data. The VGG16 model captures intricate vein patterns, while the LSTM component helps the system to handle motion-related artifacts by learning temporal dependencies. This architecture aims to improve recognition accuracy under diverse conditions, including changes in lighting and finger positioning.

Image labelling, dataset augmentation, and Motion Tolerant Deep Learning architecture are integrated to enhance system accuracy and resilience. Labelling ensures that the model captures detailed vein structures, which is critical for high-accuracy biometric authentication. Augmentation techniques, including conventional transformations and Generative Adversarial Networks (GANs), expand the dataset and improve generalization across varied conditions. The augmented dataset is then processed by a Motion Tolerant Deep Learning model, combining Convolutional Neural Networks (CNN) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for handling temporal data, which together mitigate motion artifacts when the finger moves during capture. This end-to-end approach ensures reliable performance in diverse real-world settings. When an image is given as input, the model compares it with stored templates to classify it as genuine or imposter, thus determining access based on the individual's unique vein pattern.

6. EXPERIMENTAL RESULTS AND DISCUSSIONS

The performance of the models is evaluated using benchmark datasets, THUFV [19] and SDUMLA-HMT [20] datasets, to comprehensively assess the effectiveness of these models for finger vein recognition tasks. The key performance metrics considered are accuracy, precision, recall, and F1-Score.

$$\text{Accuracy} = ((\text{True Positives} + \text{True Negatives}))/ ((\text{Total Predictions})) \quad (1)$$

$$\text{Precision} = ((\text{True Positives}))/ ((\text{True Positive} + \text{False Positives})) \quad (2)$$

$$\text{Recall} = ((\text{True Positives}))/ ((\text{True Positives} + \text{False Negatives})) \quad (3)$$

F1-Score = ((2(Precision*Recall)))/ ((Precision +Recall)) (4)

The final motion tolerant finger vein recognition model is evaluated using the performance metrics, ROC Curve, AUC, and EER. The ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings, providing insight into the trade-offs between sensitivity and specificity. The Equal Error Rate (EER) identifies the threshold where the probability of false acceptance equals the probability of false rejection.

$$\mathrm{AUC} = \int_0^1 \mathrm{TPR}(\mathrm{FPR})\mathrm{d}(\mathrm{FPR}) \quad (5)$$

True Positive Rate (TPR)= (True Positive)/ (True Positive + False Negative) (6)

False Positive Rate (FPR) = (False Positive)/ (False Positive + True Negative) (7)

Table 1 presents a comparative analysis of finger vein recognition models on the SDUMLA and THUFV datasets, focusing on the impact of image labelling and augmentation, as well as the application of a motion-tolerant model.

Table 1. Comparison of results of THUFV and SDUMLA Dataset

Database	Comparison Factor	Original	Labelled (Without Augmentation)	Labelled and Augmented Images	Labelled and Augmented Images
		VGG16			Motion Tolerant Model
SDUMLA	Number of images	3816	3816	114480	114480
	Training Time (in minutes)	64	46	210	172
	Accuracy (%)	94.30	95.45	97.11	99.76
THUFV	Number of images	220	220	7700	7700
	Training Time (in minutes)	18	13	48	32
	Accuracy (%)	92.50	96.34	98.60	99.89

The size of both the datasets significantly increased by applying augmentation, which increased the number of images from 3,816 to 114,480 for SDUMLA and from 220 to 7,700

for THUFV. This augmentation process, while increasing the training time, led to a substantial improvement in model accuracy. The accuracy of VGG16 model on the SDUMLA dataset with the original images was 94.30% and has increased to 97.11% with the labelled and augmented images. When applying the motion-tolerant model, the accuracy further increased to 99.76%. A similar trend is observed for the THUFV dataset, where accuracy increased from 92.50% to 98.60% with augmentation, and 99.89% with the motion-tolerant model. Overall, the augmentation and the motion-tolerant approach significantly enhanced the performance of the model, despite requiring longer training times. Despite the substantial increase in the number of images, the training time decreases with motion-tolerant model. For the SDUMLA dataset, the training time for VGG16 drops from 210 minutes to 172 minutes when switching to the motion-tolerant model. A similar reduction is seen in the THUFV dataset, where training time decreases from 48 minutes with VGG16 to 32 minutes with the motion-tolerant model. This reduction suggests that the motion-tolerant model is more efficient in processing the increased volume of data, due to the modified model architecture, which better handles the complexities introduced by the motion artifacts.

Figure 1 demonstrates the substantial accuracy improvements for finger vein recognition through dataset refinement and model enhancements, with the SDUMLA database achieving a final accuracy of 99.76% and the THUFV database reaching 99.89% after applying labelling, augmentation, and a motion-tolerant model.

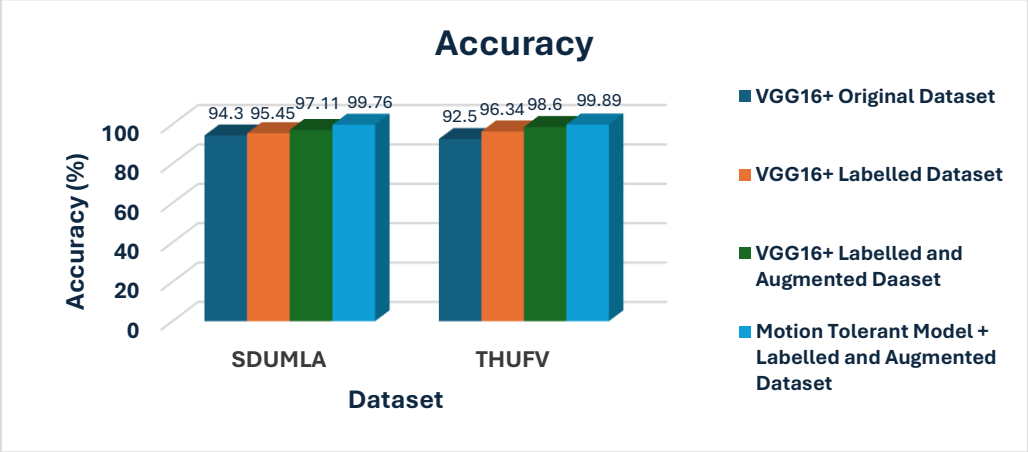

Figure 1. Comparison of Accuracy for various configurations for both datasets

Figure 2 demonstrates the precision improvements for the THUFV and SDUMLA datasets, starting with baseline precisions of 94.09% and 93.60%, respectively, using the VGG16 model.

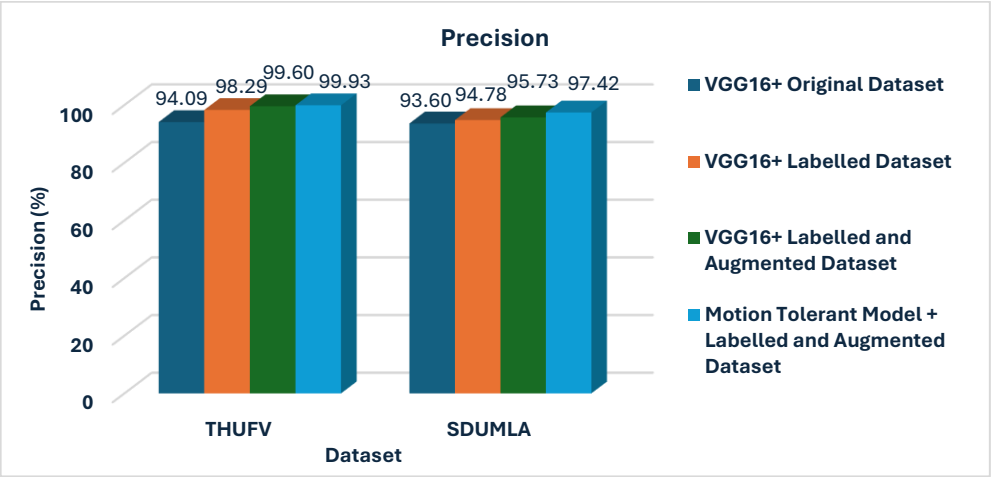

Figure 2. Comparison of Precision for various configurations for both datasets

Successive enhancements, including labelling, augmentation, and the motion-tolerant model, elevated precisions to 99.93% for THUFV and 97.42% for SDUMLA, showcasing the effectiveness of these refinements.

Figure 3 highlights the recall improvements for THUFV and SDUMLA datasets, starting at 97.64% and 92.07%, respectively, with the VGG16 model on the original datasets. Successive enhancements, including labelling, augmentation, and the motion-tolerant model, raised recall to 99.96% for THUFV and 99.76% for SDUMLA, emphasizing the impact of these refinements in boosting true positive identification.

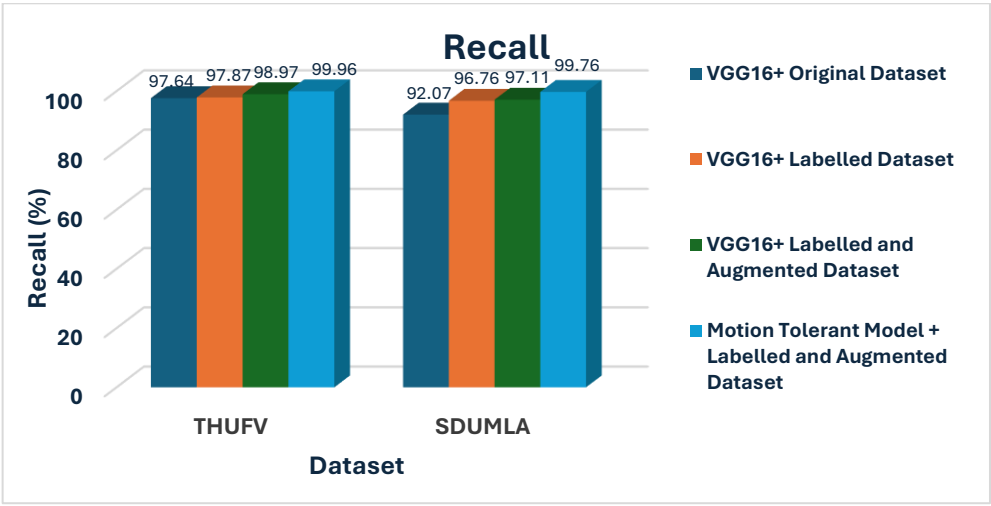

Figure 3. Comparison of Recall for various configurations for both datasets

Figure 4 shows the F1-Score improvements for the THUFV and SDUMLA datasets, showing successive gains through labelling, augmentation, and the motion-tolerant model. The THUFV dataset achieves a peak F1-Score of 99.94% (4.11% improvement), while SDUMLA reaches 98.58% (5.75% improvement), demonstrating the effectiveness of these enhancements.

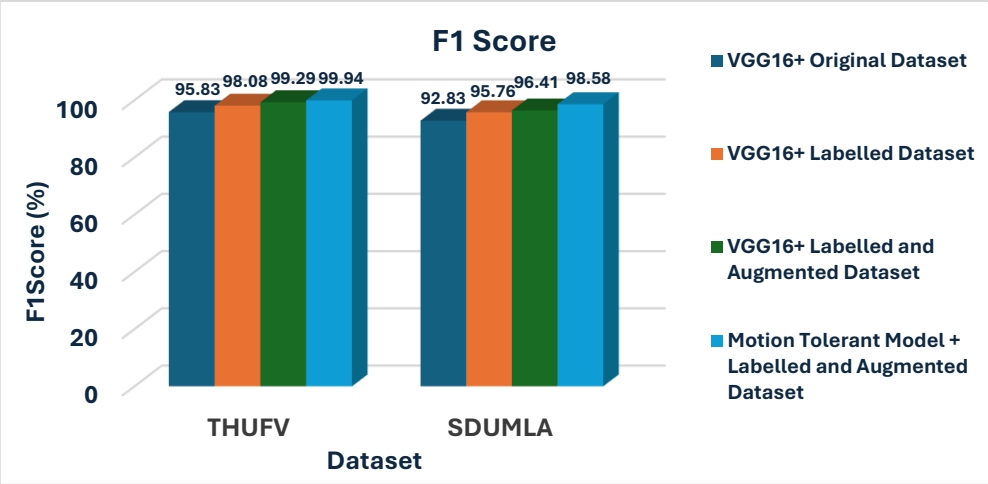

Figure 4. Comparison of F1-Score for various configurations for both datasets

Figure 5 illustrates the Receiver Operating Characteristic (ROC) curves for two algorithms (THUFV and SDUMLA) with their respective Area Under the Curve (AUC) values, demonstrating their performance, along with the Equal Error Rates (EER) highlighted for each.

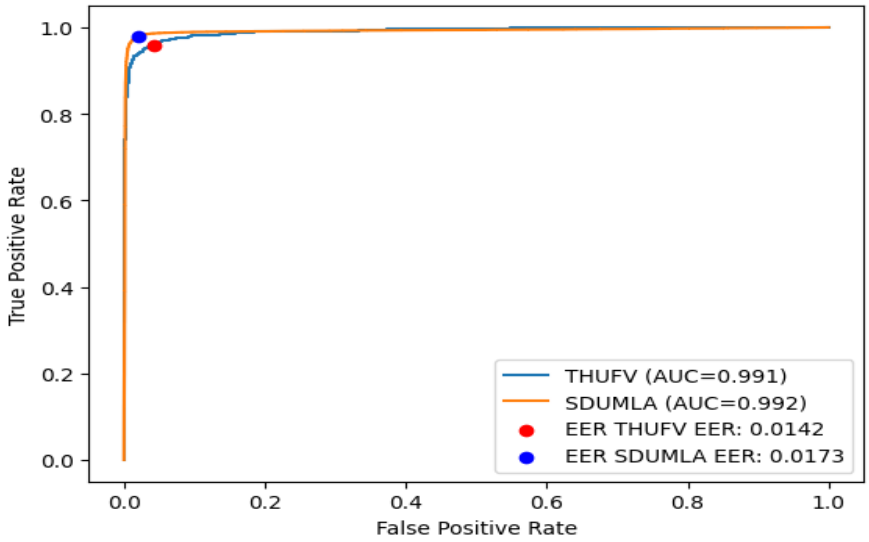

Figure 5. ROC Curve for motion tolerant model

The Equal Error Rate (EER) and Area Under the Curve (AUC) metrics for the SDUMLA-HMT and THUFV datasets shown in Table 2 demonstrate excellent classifier performance

Table 2. EER and AUC values for THUFV and SDUMLA Datasets

Dataset	EER (%)	AUC
SDUMLA- HMT	1.73	0.993
THUFV	1.42	0.991

From the table it is inferred that, for the SDUMLA-HMT dataset, the EER is 1.73%, with an AUC of 0.993, while for the THUFV dataset, the EER is 1.42%, with an AUC of 0.991, reflecting high accuracy and reliability.

7. CONCLUSION

The increasing demand for secure biometric systems highlights the importance of finger vein authentication, which offers superior security compared to the traditional methods, due to the unique and difficult-to-replicate vein patterns beneath the skin. Deep learning enhances finger vein authentication technique by enabling models to learn complex features from large datasets, improving both accuracy and robustness.

The comparison of modified UNET and VGG16 models, demonstrates that VGG16 outperforms UNET by 3.33% and 2.95% on the THUFV and SDUMLA-HMT datasets, respectively, highlighting VGG16's superior classification accuracy. The labelling of the dataset using a hybrid image labelling algorithm, boosted the model accuracy by 3.84% on THUFV and 1.14% on SDUMLA, while reducing training time. Advanced data augmentation techniques further improved the model accuracy by 6.1% on THUFV and 2.79% on SDUMLA, though it increased training time. The motion-tolerant deep learning architecture, improved the accuracy by 7.39% on THUFV and 5.45% on SDUMLA over VGG16, demonstrating high reliability through improved ROC, AUC, and EER metrics. Collectively, these advancements, through hybrid labelling, augmentation and motion-tolerant architectures, significantly improve the performance, robustness, and reliability of finger vein recognition systems, especially for contactless scanning applications.

8. ORGANISATION OF THE THESIS

The thesis is organised as follows: **Chapter 1** describes the overview, motivation, problem definition, research objectives, scope, and contributions. **Chapter 2** studies and analyses the literature surveys related to the research work. **Chapter 3** explores the performance of the modified UNET with that of the VGG16 model, with a thorough analysis of various performance metrics. **Chapter 4** introduces a novel hybrid algorithm for finger vein image labelling. **Chapter 5** discusses the use of conventional image transformation techniques and the implementation of conditional Generative Adversarial Networks (GANs. **Chapter 6** focuses on the development of an adaptive recognition model that combines the VGG16 architecture with Long Short-Term Memory (LSTM) networks. **Chapter 7** summarizes the performance analysis of VGG16 and motion tolerant deep learning model on original datasets and labelled and augmented datasets. **Chapter 8** concludes the research work and provides the scope of future enhancement.

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List of Publications

1. Amitha Mathew, Amudha P. (2024). Enhancing Finger Vein Authentication through Deep Learning: A Comparative Study of U-Net and Sequential Models. Journal of Advanced Research in Applied Sciences and Engineering Technology, 47(1), 230-243. https://doi.org/10.37934/araset.47.1.230243 (SCOPUS)

2. Amitha Mathew, Amudha P. (2024). Improved Finger Vein Recognition Using Generative Adversarial Network and Transfer Learning. Journal of Nanoelectronics and Optoelectronics, 19(10), 1053–1062 https://doi.org/10.37934/araset.47.1.230243 (SCIE)

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4. Amitha Mathew, Amudha P. Finger Vein Image Labelling using Hybrid Algorithm., Proceedings of International Conference on Emerging Trends in Industry 4.0 and Sustainable Concepts 2023, pp 268-271, ISBN 978-93-5782-946-5